Intelligent Transportation Systems With Diverse Vehicles

14

14.1 Introduction

Transportation systems are amalgamations of numerous subsystems which operate harmoniously with each other for overall efficiency and ease of travel. It is hence encouraging to intelligently operate each of these subsystems for efficient travel and to further exchange information between these subsystems for higher efficiency. Many factors play a major role in regulating traffic and hence need to be intelligent and adaptive towards changing traffic trends. This includes the mechanisms to handle traffic lights, intersection management, overtaking policies, speed-lane policies, reservation policies etc. Each of these management systems and policies largely depends upon the kind of traffic that is operating in a region. Increasing autonomy in the vehicles and the transportation infrastructure facilitates engineering innovative solutions that make the best out of available information and enable sharing information amongst transportation subsystems.

The core interest behind the book is to study a traffic system that operates without speed lanes. It was advocated that such a traffic system is largely caused due to diversity between vehicles. A macroscopic study of the entire transportation system operating without lanes is currently not possible. However, it is still intriguing to study the transportation system when operated with diverse traffic, which is the theme of this chapter. Although it would be incorrect to state that the concepts and results presented here would be applicable for transportation systems without lanes even though both systems are triggered by diversity of traffic, some indications can always be drawn. More importantly, the focus of the chapter is towards the design of algorithms at the transportation level which perform well in conditions of high diversity in vehicles.

Section 14.2 discusses some very interesting works in the intelligent management of transportation systems, particularly from the point of view of routing. Section 14.3 assumes the vehicles have some communication with a central transportation authority or other vehicle infrastructure system. This is similar to the assumption of communication placed in chapters ‘Optimization-based Planning’, ‘Sampling-based Planning’, ‘Graph Search-based Hierarchical Planning’ and ‘Using Heuristics in Graph Search-based Planning’; however, the assumption is softer here. Such an assumption can lead to a variety of ways in which the traffic can be managed which would not be possible in the case in which the vehicles are not connected. The chapter discusses numerous such possibilities through simulations.

Section 14.4 does not assume any communication which means any number of human-driven vehicles can be on the road. This makes many of the possibilities introduced in Section 14.3 impossible to implement. The most important problem in such a

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context for a macroscopic study is vehicle routing. Effective routing can avoid road congestions and hence inefficiency in the transportation system. The aim is to study an urban kind of transportation system, for which the design of an effective routing technique is displayed.

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14.2 A Brief Overview of Literature

Here, some of the notable works in the intelligent management of the transportation system are very briefly discussed. Diversity is an important aspect which most of these works do not particularly address. These works make different elements of the transportation system intelligent and thus result in a better traffic efficiency. Routing and related decisions are particularly important for effective traffic operation.

The complete road network graph can be viewed as a Markov network with the route as a Markovian process. Kim et al. (2005) presented their results to routing. The model could account for dynamic traffic, and hence congestion could be monitored. Wahle et al. (2000) used Cellular Automata and defined various traffic behaviours like braking, accelerating, avoiding obstacles etc. as rules. Based on this approach the authors showed a routing strategy such that the entire traffic was more distributed. In another related approach, Furda and Vlacic (2011) also use Automata for system modelling. The authors exhibited vehicular behaviours including maintenance of position on the road, maintenance of a safe distance from other vehicles, collision avoidance etc. Current behaviour was selected using Multicriterion Decision-making.

Inspired by the ant algorithms, digital pheromone is another popular mechanism by which traffic dynamics in a road network may be modelled and decisions may be made. Ando et al. (2006) represented various driving actions by a digital pheromone distribution. These pheromones gave an indication of traffic congestion. The same information was used for routing decisions. Narzt et al. (2007) also used the notion of digital pheromones. Their model used micro simulations with a decentralized routing strategy for vehicular motion.

In terms of route planning in a static sense, when the given road network graph becomes too complex, it is viable to use some hierarchical planning. Song and Wang (2011) employed heuristics to divide the entire road network into hierarchical communities. Each community marked a highly connected region. Li et al. (2009) represented a graph in a multilayered approach with edges between the layers. Voronoi diagrams were used as the basis for hierarchical separation of the road network map. Tatomir and Rothkrantz (2006) presented another hierarchical approach. Their algorithm divided a road network into zones with identified road links connecting the zones. The authors used an ant-based swarm algorithm to find the shortest route. In addition, the authors displayed how the time of journey may be computed when rerouting in accident situations.

Fawcett and Robinson (2000) displayed a system which monitored live data with relevance to the available road infrastructure and the mechanism by which these data may be made available to route planning of the vehicles. Kesting et al. (2008) looked at the problem of traffic congestion and proposed a model wherein vehicles could adapt their driving model parameters based on the available information of traffic flow.

In a situation in which the number of vehicles is too large and the road infrastructure is limited, reservation seems a viable alternative. Congestion may be avoided by a careful reservation strategy. Dresner and Stone (2004) studied a subset of this problem of intersection management and proposed a scheme in which the autonomous vehicles could navigate by reservation irrespective of the traffic signal states. The authors further extended the model to incorporate learning behaviour and market economics of reservation (Dresner and Stone, 2006, 2007). Vasirani and Ossowski (2009) continued this work by presenting a market economy model for reservation. For roads, an approach similar to reservation was used by Reveliotis and Roszkowska (2011) who modelled the entire road infrastructure as resources with a judicious resource allocation algorithm.

14.3 Semiautonomous Intelligent Transportation System for Diverse Vehicles

For reasons of safety, driving efficiency and sometimes driving comfort, much research is now being done in the domain of driving assistance systems and autonomous vehicles. Autonomous vehicles are technologically more advanced and are capable of driving on their own without any human input, making all driving decisions on their own. *Semiautonomous vehicles*, however, provide limited capabilities, restricted to either or all of automated parking, overtaking, lane following etc. State-of-the art research in these domains showcases a promising future in which vehicles increasingly become more advanced, to the extent that most vehicles on the road will be semiautonomous with communication abilities, access to advanced travel information and dynamic route guidance systems, amongst other safety and decision-making systems. In reality though, nonintelligent vehicles may still exist in small numbers for a very long time. A fully autonomous scenario, with only autonomous vehicles is also a possibility, although this may take a much longer time to materialize.

Vehicles with different levels of autonomy have different capabilities related to vision, control and reaction time, all of which lead to capabilities to drive at different maximum speeds. Autonomous vehicles may especially be designed for different commercial or business requirements due to which they may vary in their type, make and performance, leading to different driving speeds. For semiautonomous vehicles, driving speeds also depend upon driver preference, passenger preference, purpose of travel, social stature etc. All of which leads to different vehicles driving at different speeds. In fact, at present traffic showcases limited *diversity in driving speeds*, wherein different drivers prefer to drive at different speeds, leading to lane changing, overtaking and a distribution of traffic across lanes roughly as per the preferential driving speeds. Increasing levels of autonomy are though very likely to increase this speed band, making traffic more diverse in terms of speed capabilities.

Intervehicle communication (Sen and Matolak, 2008) systems help a group of vehicles to talk to each other and share information which provides advantages including collision warning, obstacle alert, cooperative obstacle avoidance etc. *Vehicle–infrastructure communication* (Ma et al., 2009) meanwhile enables a vehicle to communicate with a transportation infrastructure found on the road. Such a system may be useful to communicate traffic or road conditions to the vehicle. Communication helps vehicles to make optimal decisions at the local and global levels, while reducing any uncertainties. Having extra information via communication, unknown to the driver's or the vehicle's normal vision, is always helpful in decision-making. Here, the focus is not only on making a vehicle's personal plan better, but in enabling vehicles to collaborate to make the overall transportation system better, even if it is at the cost of one's own personal plan.

Traffic systems play a major role in regulating the movement of vehicles in any country. In most scenarios, static traffic rules lead to reasonable traffic management for most general driving. Traffic may further be managed by making rule changes for certain days and times (eg, heavy vehicles at night only) or to cope with certain scenarios (eg, possibly a large number of vehicles before/after a concert or sporting event). These rules need to be effective as they impact a large number of vehicles. However, in the case of semiautonomous vehicles, this allows for a transportation system-wide communication between all entities, thereby enabling a *central transportation authority* to *dynamically* regulate traffic as per the available information or traffic policies. Alternatively, an intelligent system may be placed to constantly monitor traffic, anticipate traffic conditions and make traffic regulating decisions, which may be communicated to the vehicles for them to follow.

Traffic simulation allows the study of various ways or rules by which traffic can be regulated. Traffic simulation systems are classified into microscopic systems, macroscopic systems and mesoscopic systems (Helbing et al., 2002). The approach towards this domain is microscopic in nature, in which the individual vehicle behaviour is considered, when planned amongst a group of vehicles in a scenario.

This work continues the discussion on motion planning for autonomous vehicles in a traffic environment with diverse speed capability vehicles and operating in unorganized traffic. The solutions were largely restricted to a straight road. It was observed that diversity leads to interesting driving behaviours. It is hence encouraging to study the effect of diverse unorganized traffic on the overall transportation system. This requires the need for a traffic simulator working with unorganized traffic and diverse vehicles. Creating a complete simulation system for unorganized traffic requires solving complicated subproblems. Here, a simulation system for diverse and organized traffic is presented.

The simulation system described here was built by taking a futuristic view in which *most of the vehicles would be semiautonomous* within an *intelligent transportation infrastructure*. A semiautonomous vehicle may be defined as one that can be networked, with the ability to take basic driving instructions which may be implemented by a human driver or the autonomous vehicle itself. The aim is to exploit all possibilities with such traffic by closely observing each and every transportation entity. This notion opens a pool of new possibilities and issues, some of which are presented. Although vehicles being semiautonomous may not necessarily be a requirement in all cases, it will certainly benefit the system in making dynamic and fast changes, which cannot be done in the present traffic system.

With this simulation, the approach is to introduce a number of *concepts* in the present traffic system and to study the behaviour of vehicles under these concepts by a simulation. By this, the effectiveness of the introduced concepts could be measured against the rules presently in the system for a diverse vehicle scenario. At the same time, the attempt was to make a traffic simulation system that accounts for the ability to statically (at the start) or dynamically specify the applicability of all these concepts on various roads. The simulator also provides a base for current and future research to make traffic systems more sophisticated, with the presented assumptions.

In this simulator, it is assumed that the task is to enable a large number of vehicles to reach their destination from their source. The road network map is already available within the system. Each vehicle starts from its own source and attempts to reach its destination in the shortest time possible, in *cooperation* with the other vehicles. The vehicles emerge from their source at a predefined time and leave the map on reaching their destination. At any time during the simulation process, the position of all the vehicles is assumed to be known. Further, the vehicles can communicate with the *central information system*, which helps them in decision-making. The key takeaways of the algorithm are summarized in Box 14.1. The major concepts are also summarized in Box 14.2.

Box 14.1 Key Takeaways of the Semiautonomous Intelligent Transportation System Approach

- The approach presents an *integrated study* of an intelligent transportation system covering all the various concepts which are separately studied in the literature.
- The study proposes *architecture of the transportation systems* of the future covering both decentralized vehicle control and centralized management control.
- The approach is designed for *diverse semiautonomous vehicles* operating in a scalable environment, which is the likely future of the transportation system.
- The approach is a positive step towards creation of a *traffic simulation tool* for diverse and unorganized traffic.

Box 14.2 Key Concepts of the Semiautonomous Intelligent Transportation System Approach

- **Assumptions**
  - All vehicles are semiautonomous, or all can communicate
  - All vehicles can be tracked
  - There might still be some human-driven vehicles
  - Vehicles have very diverse speeds
- **Key idea**
  - Explore all the possibilities with such assumptions
  - Enable vehicles to cooperatively reach their destinations in the best way
  - Make transportation rules dynamic
- **Systems**
  - *Traffic Light System*, to immediately change light when a queue gets empty, and to subsequently allow traffic from the road with the most-waiting vehicle.
  - *Speed Lanes*, to dynamically vary the speed limits of lanes based on the diversity of the vehicle speeds.
  - *Route Planning*, to avoid building up of congestion on any road.
  - *Reservations*, to give reserved rights to some vehicles for a lane or for the entire road.

Traffic lights are an important aspect of a traffic management system. They ensure that vehicles reach their destinations on time, at the same time avoiding congestion. Both the order and duration of operation are important. The manner of handling traffic lights is discussed in Section 14.3.1. Similarly, *speed lanes* play a major part in the distribution of traffic. This especially becomes important in the case of vehicles with diverse speed capabilities. Deciding the speed limits for individual lanes is important, which in this system is discussed in Section 14.3.2. *Route planning* deals with deciding on the roads to use to reach the destination. *Continuous replanning* enables escaping from densely crowded roads, traffic regularization and the avoidance of traffic jams. Section 14.3.3 presents the route-planning algorithm used in this system. Increased traffic density, slow traffic and a wide diversity in speed capabilities, especially at some times of the day and for some roads, necessitate the need to use roads as a *reserved* infrastructure. In Section 14.3.4 the mechanism by which a road or a lane may be made available only by means of making a reservation is discussed. This enables important vehicles to reach their destination as early as possible, which includes emergency vehicles. Section 14.3.5 presents the general architecture of the system.

14.3.1 Traffic Lights System

Traffic lights constitute one of the most important aspects of a traffic system. The waiting time for traffic lights to turn green may constitute a significant proportion of the time of journey. Efficient operation of traffic lights can lead to overall traffic efficiency.

14.3.1.1 Concept

Presenty employed traffic light systems allow traffic going from multiple sources to travel within a specified time. Usually this time is prespecified to a threshold value. Common problems include having to wait for one's turn to cross when no other vehicle coming from the other direction, an equal waiting time for traffic on high-density roads and low-density roads, fixed traffic light operation times during the day, nonadaptability to changing traffic trends, having to wait for too many traffic light changes whilst travelling on a high traffic-density road etc. It is evident that intelligent traffic lights operating within an intelligent transportation system are capable of overcoming these problems.

The proposed traffic light system considers both the number of vehicles as well as the operation time. It is assumed that the number of vehicles waiting to cross at each crossing is known in advance. In the case of networked semiautonomous vehicles, this task is trivial as the position of the vehicles is reasonably well known by Global Positioning System (GPS) or a local mapping algorithm. Additionally, sensors at the crossing region may help record the same data. Assume a crossing c with intersecting roads $R = \{R_1, R_2, R_3, R_4,...R_n\}$. Vehicle information is noted in a data structure Q_c, which maintains a queue of all vehicles waiting at the crossing region. An entry comprises the triplet $<V_i, R_i, t_i>$ denoting the vehicle V_i entered the crossing scenario (when it is ready to go over the crossing) at time t_i from road $R_i \in R$. The data structure is updated for every vehicle (V_i) entering (Eq. [14.1]) or leaving (Eq. [14.2]) the crossing scenario:

$$Q_c = Q_c \cup \langle V_i, R_a, t_i \rangle \quad [14.1]$$

$$Q_c = Q_c - Q_c[V_i] \quad [14.2]$$

in which $Q_c[V_i]$ is the entry of V_i in Q_c.

The traffic lights operate in a manner such that at any time only one road has the green signal, whereas the signal for all other roads is red. All vehicles on the road in possession of the green signal can travel, irrespective of their exits. Lateral time is employed to clear the crossing region between light changes. The objective of the traffic lights is to reduce the maximum waiting time for any vehicle. Hence, the order of traffic light changes is such that each change allows all traffic from road R_a in possession of the *longest waiting vehicle* at crossing c to cross. Let D_c denote the road with the green traffic signal, which changes as per (Eq. [14.3]).

$$D_c = R_i, i = \text{argmin}_{i,\langle V_i, R_i, t_i \rangle \in Q_c} t_i \quad [14.3]$$

Traffic lights change as per the stated order if a traffic light change event (say E_c) occurs. After every change, the traffic lights stay in the same mode until a maximum of

η vehicles have crossed or for a maximum of T units of time. Here, η is taken as the minimum of a threshold value (η_{th}) and the present queue size ($|Q_c[D_c]|$) for vehicles originating from the road which is currently green (D_c). T is the time threshold which is a constant. If no vehicles are left on the road which is currently green, the traffic lights change. The change may however only occur if currently no other vehicle is in the crossing area. Leaving this lateral time ensures that no deadlock exists in the crossing region. The prerequisite for a change to occur is given by Eq. [14.4].

$$E_c = T_c \geq T \vee \eta_c > \eta \vee |Q_c[D_c]| = \phi \qquad [14.4]$$

Here, T_c is the time elapsed since the last change and η_c is the number of vehicles that passed since the last change.

Limiting both the *maximum time* and the *maximum number of vehicles* enables much better control of traffic when it contains diverse vehicles. Because the vehicles are semiautonomous, this is realizable. An important criterion here is to keep η_c as the minimum of the current queue size and a threshold. The effect of this is to discourage a newly entered vehicle from passing over the crossing region without waiting. This is because such a crossing might be at the cost of another waiting vehicle. If there are no other waiting vehicles, any change would automatically be in favour of the newly entered vehicle, which would be allowed to move. In this way, the heuristic of minimizing the waiting time can be realized.

14.3.1.2 Simulations

The purpose behind the simulations was to test the working of the proposed system under diverse traffic conditions. A map was employed with a crossing at the centre. A random number of vehicles were generated, each with its own speed capability, and these vehicles were made to travel from one road to the other over the crossing. The emergence time of the vehicles was randomly fixed. This system of traffic light operation was compared to a system in which the lights were changed at regular intervals of T units of time, which is the method frequently encountered in practice. In such a strategy, a lot of time could be wasted if the light is green yet no vehicles need to cross. The simulation system generated vehicles within random small time intervals that are uniformly distributed.

Another simpler traffic light change system was also studied. The change condition was kept largely as in Eq. [14.4], with the only difference being that changes were produced in a *cyclic order*, rather than that proposed in Eq. [14.3]. In all the simulations, the average time of travel was used as a metric. These three algorithms were simulated for varying numbers of vehicles. A smaller number of vehicles in a scenario meant less densely occupied roads and vice versa. The resultant graph between the number of vehicles in the scenario and the average time of travel is shown in Fig. 14.1A. Every point on the graph represents a scenario with random entry time, exit time and speed. Hence, the randomness has been smoothed by plotting a trend line produced by the moving-average method. The simulation used arbitrary units of

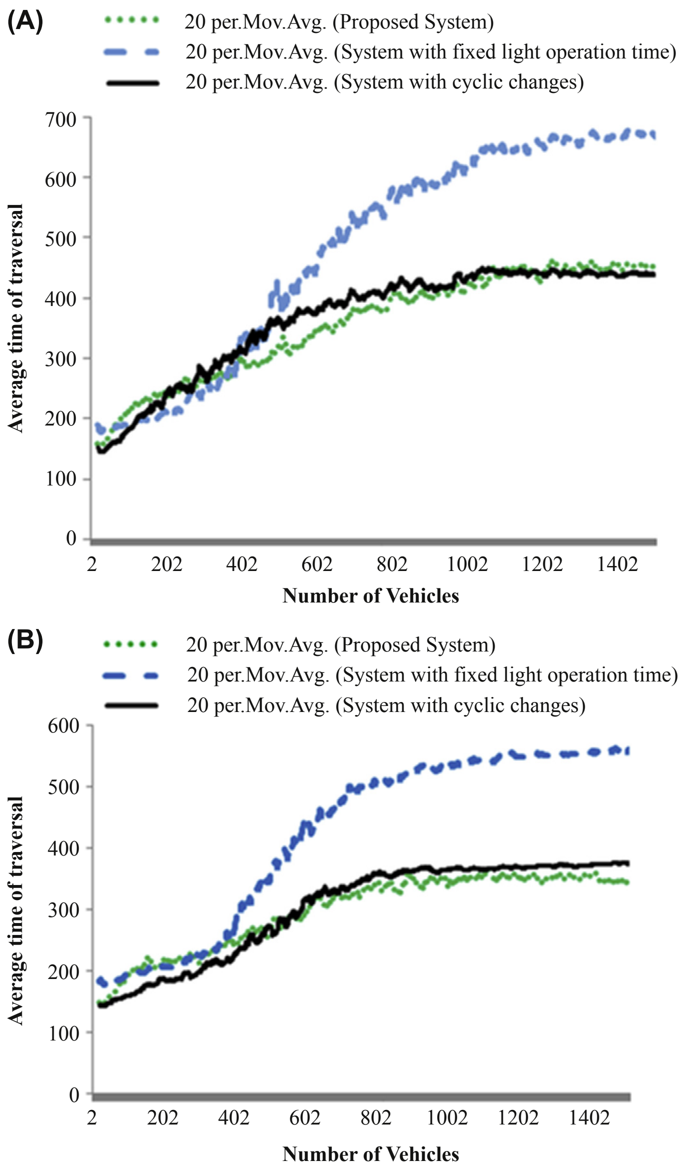

Figure 14.1 Comparative analysis of traffic-light system for different numbers of vehicles: (A) traffic from all sides and (B) traffic from one side blocked.

distance and time which are specific to the simulation tool and can relate to real-world units proportionately.

The general trend in all the curves was an increase in the average time of traversal with increasing numbers of vehicles, until this time became a constant. The increase was due to increasing traffic density. On reaching a congested (saturated) traffic density, any subsequent increase in the number of vehicles had no effect. The curve with fixed traffic-light operation time was though much more inefficient when compared to the other two approaches which showed almost the same trend. That said, for middle-density traffic the proposed system did exceed the system with cyclic crossing changes in terms of average traversal time. Small changes in average traversal time could though be regarded as insignificant, considering the random nature of the generation of vehicles. The significance of this was further highlighted by disallowing traffic generation from one side of the road, while the traffic lights operated in the same order. The resulting graph is shown in Fig. 14.1B. It is clear that the difference between the approaches is magnified, which shows the clear limitation of having fixed traffic-light operation times.

Two important parameters in the approach govern the algorithmic performance. These are the time threshold (T) and the threshold number of vehicles to cross (η_{th}). Both these parameters are analysed. In the first experiment, T was varied and the average traversal time for the different situations was compared. The factor η_{th} was set to infinity, so that it had no effect on algorithmic performance. The study was broken down into a densely packed road (with 2000 vehicles) and a lightly packed road (with 250 vehicles). The resulting graph produced is shown in Fig. 14.2A for a densely packed road and Fig. 14.2B for a lightly packed road.

Fig. 14.2A shows that the general trend was an initial decrease in the average traversal time as the time threshold was increased, which then became a steady value. Increasing this factor causes fewer traffic light changes, which as a result reduces the lateral switching time. The decrease reduces further as a very small proportion of vehicles are affected by the lateral time and the effect is balanced by the gain in reduced traversal time of the vehicles on the other roads at the crossing. This certainly suggests that making relatively few changes in traffic light signals could actually be beneficial overall. In a practical sense, it would be sensible for no vehicle to stop at a crossing for more than two traffic light changes, which is practically observed mainly due to lower traffic density. However, it may be noted that too few changes might drastically increase the wait time for some vehicles, while lowering the time for some other vehicles. Hence, someone may be lucky enough to queue when the lights were about to change to green, whereas another person might arrive at the front of the queue when the traffic lights have just changed to red. Maximum wait time is not a factor studied here, but in reality may be a value for a parameter setting.

The traversal time for fixed light operations is much higher than the other two cases, which seem to nearly follow each other. The entire scenario has start and end stages in which the density is fairly low and a central stage of high density of vehicles. In the start and end stages the fixed light operation time algorithm performs very poorly as compared to the other two. Spending excessive time on a road with no vehicle in the queue is the major reason for this. Further, in the central stage, the other two approaches put stress on allowing the motion of vehicles which were in the queue at the time of a change (a rule used in light operation), whereas the fixed light operation time algorithm allows motion of any newly entrant vehicles as well. This decreases its effectiveness.

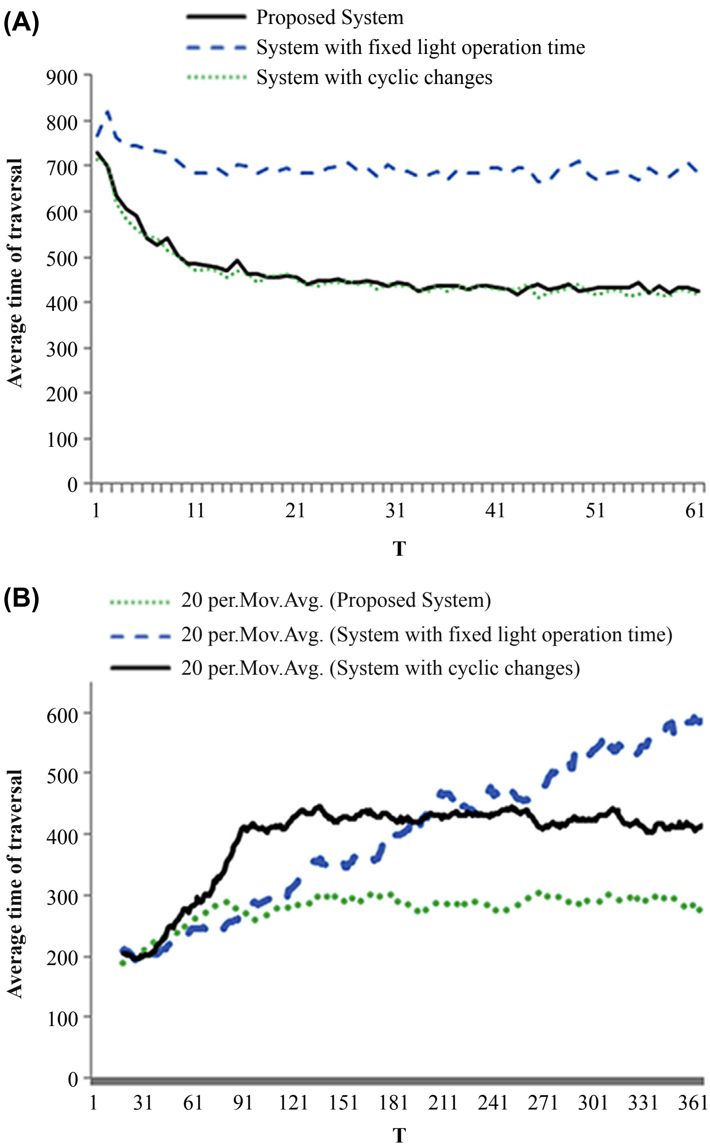

Figure 14.2 Comparative analysis of traffic lights system for different values of *T*: (A) densely occupied scenario and (B) lightly occupied scenario.

The same experiments performed with a lightly packed scenario show a different trend. The resulting graph is shown in Fig. 14.2B. The fixed light change algorithm showed a general increase in traversal time in line with increasing *T*. This was because of the waiting time when the queue was empty or was predominantly occupied by vehicles that had just arrived into the scenario and the traffic light was not changed. This waiting time increased with an increase in T making the algorithm consistently inefficient. The other two systems however showed similar trends, with the proposed system being better as the value of T was increased. The increase of this factor in this case had the effect of increasing the average traversal time, which soon settled around the same value. The increase was due to the fact that the road was lightly occupied and the increased time meant fewer changes which, as a result, increased the waiting time for vehicles. After some increase, the changes were caused only due to the vehicles in the queue being cleared rather than the time threshold. Hence, this factor, on further increase, was not used. It may be observed that increasing T increases the wait time for vehicles in a queue (unpreferred) but at the same time decreases the overheads of excessive crossing changes (preferred).

The other parameter of study was η_{th}. It is natural that this factor plays no role in the system with fixed light operating times, and hence this study did not consider that system. This factor is discussed here separately for low- and high-density roads. For high-density roads, there was a little decrease in traversal time on initial increase of this factor, but this soon became constant. The increase of this factor leads to fewer traffic-light changes and hence less overhead. The corresponding graph is plotted in Fig. 14.3. The irregular trends are because the actual points, rather than a trend line, are plotted. Experiments with low-density roads showed that the vehicles continued to travel without unnecessary queues. Because traffic lights did not wait in the case that the initial queue had cleared, the simulation continued. Hence, this parameter had no effect on the performance and showed constant results for any value of set parameter.

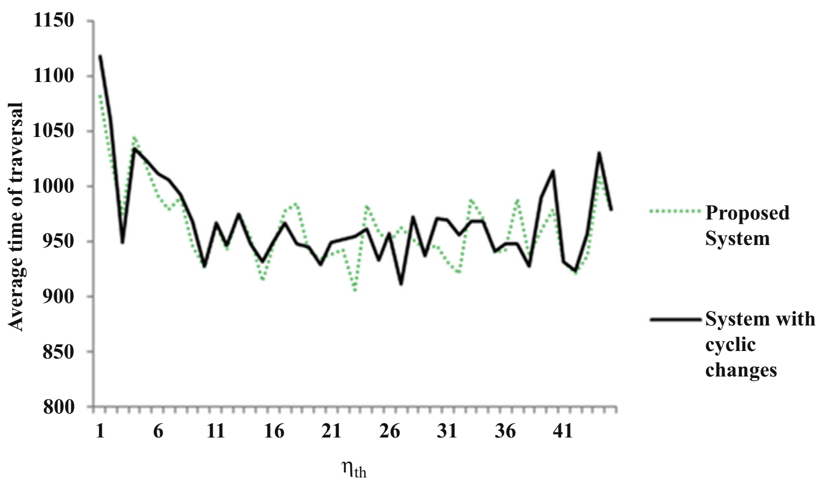

Figure 14.3 Comparative analysis of traffic-light system for different values of η_{th}.

14.3.2 Speed Lanes

The idea of assigning different speed limits to different lanes is an important concept that especially comes into play if the traffic on a road has a high diversity in vehicles ranging from those with low speeds to those with high speeds. Having slower vehicles migrate onto all lanes clearly would make the traffic slow on all lanes, which is not good for higher preferential speed vehicles. Similar to the case of fixed traffic light operational times, the optimality of fixed speed limits for different speed lanes is questionable. The intention here therefore is to *dynamically adjust the speed limits* of the various lanes. The central system vigilantly changes the speed limits depending upon the speed capability of the set of vehicles on the road, as they arrive and exit. The optimal speed limits of the lanes at any time may be a complex function depending upon the preferential speed distribution of the road. The concept is however simplified to some extent by assuming a uniform distribution. Let $V = \{V_i\}$ be the set of vehicles on a road R_a. Let s_i denote the preferential speed of a vehicle V_i. Let $\min_i(s_i)$ and $\max_i(s_i)$, respectively, be the minimum and maximum preferential speeds exhibited by any vehicle on the road. Let the road have b speed lanes. The speed limits of the various speed zones (in increasing order of limits, measured from the left to right) are allocated by Eq. [14.5]:

$$L_j = (1 - w_j)\min_i(s_i) + w_j\max_i(s_i) \tag{14.5}$$

in which: $w_1 < w_2 < w_3 \ldots < w_b$; $w_1 = 0,\ 0 < w_2,\ w_3, \ldots w_b \leq 1$. w_j is the weight associated with the lane j.

It is important to realize that unlike the current traffic system, here the speed limit implies a lower bound, which is the least preferential speed that a vehicle must possess to drive in a particular lane. The upper bound is, however, set as infinity for every lane. Semiautonomous vehicles may have their preferred speed set as per their capabilities as it would not be appropriate to force them drive subject to lower limits. This concept by itself results in *overtaking capabilities* for a vehicle with a reasonably high preferred speed. A vehicle on seeing another vehicle moving with a lower speed may opt to change its speed lane and drift rightwards (the driving rule is assumed be on the left, which means overtaking on the right is preferred). After some time the overtaking vehicle would be ahead of the vehicle being overtaken. At this time, if the vehicle finds another slower vehicle in front of it and no higher-speed lane is available, it can always drift leftwards and return to its original speed lane. This is because the upper speed-limit bound was set to infinity, and it is quite valid for a high-speed vehicle to drive on a speed lane with a lower bound. This would then complete the overtaking procedure. It is evident though that driving with a higher speed in a low-speed lane may not be optimal, and hence eventually the vehicle would seek a chance to drift to the higher speed lane.

The system was studied via simulations. The map given was a simple straight road on which different vehicles were generated at different times with their own speeds. The road had two lanes (for each side of traffic − outbound and inbound). This made the lower bounds of the speed limits of the two lanes as 0 and $(1 - w)\cdot$

$\min_i(s_i) + w \cdot \max_i(s_i)$ by Eq. [14.5]. First, the parameter w is studied. The study was performed separately under low and high-density conditions. The system was compared to a system that had no speed lanes and hence any vehicle could drive on any lane (even though the parameter w plays no role for a system without speed lanes).

The graph produced on a densely packed road (with 2000 vehicles in the scenario) is shown in Fig. 14.4A. As the factor w was increased, so did the speed limit for the high-speed lane. As a result, fewer vehicles were allowed to move to it. Although this decreased the time of travel for the vehicles using the high-speed lane, at the same time it led to the high-speed lane being underutilized. As a result,whenever the speed limit was increased, the decrease in travel time for the vehicles in the high-speed lane was averaged out by an increase in travel time for the vehicles in the low-speed lane. Conversely, keeping this factor close to 0 makes the system equivalent to one with no speed lanes.

The same patterns may be observed in Fig. 14.4A. Lightly packed roads ideally do not require speed lanes as the various vehicles can easily pass each other without resulting in obstruction. In such a scenario, high-speed vehicles lose out as they have to spend time overtaking slower vehicles. However, this lost time is very small in comparison with the time that the slower vehicles gain by having access to the

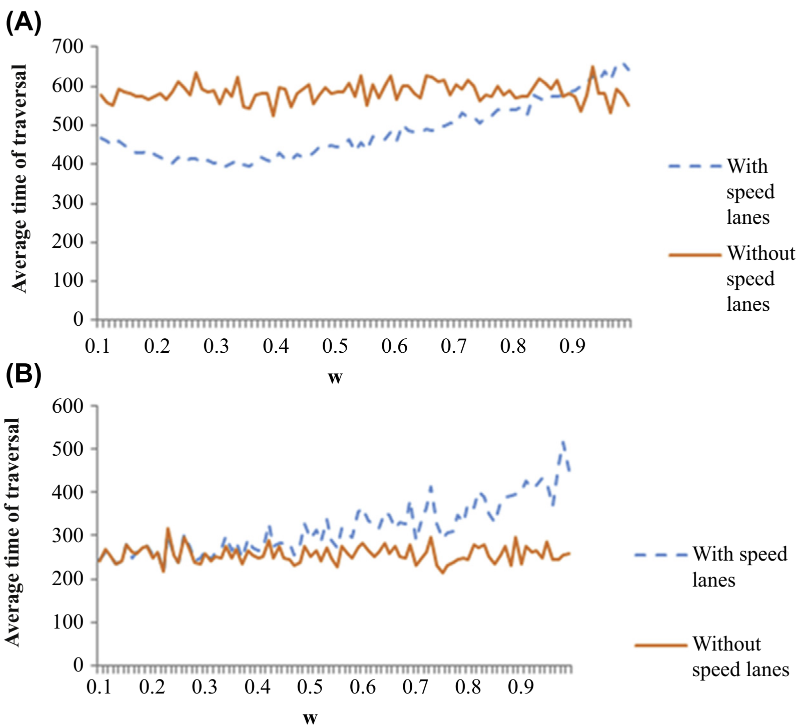

Figure 14.4 Comparative analysis of speed-lane system for different values of w: (A) densely occupied scenario and (B) lightly occupied scenario.

high-speed lane which increases the traffic bandwidth. The results of lightly packed road are shown in Fig. 14.4B.

Diversity of traffic is a major factor that plays an important role in the speed-lane system. To better test the system, the effect of a varying diversity of vehicle speeds on the algorithm performance is also studied. The simulation tool produced vehicles the speeds for which lay within a specified upper and lower bound. The first experiments were done by changing the upper bound (at the same time keeping the lower bound fixed to a value of 0.2 unit distance per unit time, arbitrary units) and then subsequently experiments were done by changing the lower bound (keeping the upper bound fixed to a value of 1 unit distance per unit time, arbitrary units). The corresponding graphs are shown in Fig. 14.5. Here, the time of traversal was compared with that of a fixed speed-lane system, in which the speed limit (lower bound) of the high-speed lane was fixed to a value of 0.5 unit distance per unit time. The general decrease in time in both cases is due to the increased average speed of the vehicle. It may be easily seen that the variable speed-limit system nicely adapts the speed limits for enhanced performance.

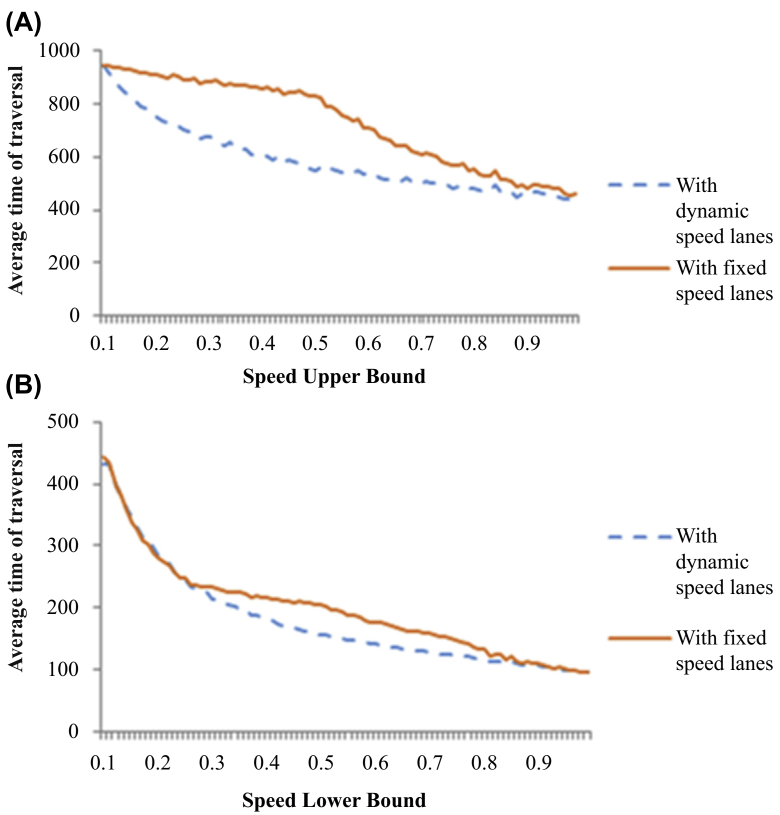

Figure 14.5 Comparative analysis of speed-lane system for different diversities of vehicles: (A) variable speed upper bound and (B) variable speed lower bound.

14.3.3 Route Planning

Routing plays a major role in distributing traffic across the road network, enabling every vehicle to reach its destination in the shortest possible time in cooperation with the other vehicles. In reality, it is common to have many vehicles using a popular road which enables quick access to a particular destination. This, however, leads to increased *congestion* and lower driving speeds for all, thereby resulting in reduced performance. Not considering other vehicles while planning one's own route may hence lead to poor results. The solution is to *distribute traffic* wisely on the roads, exploiting the entire transportation infrastructure for collective travel. An alternative longer road may be used, if it appears to have lower traffic density as compared to the main road. However, if the alternative road is too long, the choice may not be beneficial.

A *Uniform Cost Search* algorithm is used to route plan every vehicle in this approach. The aim of the Uniform Cost Search algorithm is to minimize the time of travel of all vehicles. Any road being selected for travelling is added a penalty which is proportional to the traffic density of the road. The central information system does know the current traffic density of the roads, but not the expected traffic density at the expected time of arrival of the vehicle on the roads. Hence, the traffic density is predicted using the historical information of traffic flow. For roads near the current position of the vehicle, the current density is of a higher relevance, as it would not change much till the vehicle arrives at that road. However, for roads far away from the current position of the vehicle, the prediction from historical data is more important as the current traffic scenario could change drastically. Hence, the expected density at road R_a at time t may be given by Eq. [14.6].

$$\rho(R_a, t) = \begin{cases} \rho_{\text{current}}(R_a) & t \leq \beta \\ \rho_{\text{historic}}(R_a, t) & t > \beta \end{cases} \qquad [14.6]$$

Here, $\rho_{\text{current}}(R_a)$ is the current traffic density and $\rho_{\text{historical}}(R_a, t)$ is the predicted traffic density. β is the time until which the current traffic density is reliable. The total cost computed for a node c_1 when expanding from a node c_2 connected by a road R_a for vehicle V_i may hence be given by Eqs [14.7] and [14.8].

$$t(c_1) = t(c_2) + \frac{|R_a|}{s_i} \qquad [14.7]$$

$$f(c_1) = f(c_2) + \alpha \cdot \rho(R_a, t(c_1)) \qquad [14.8]$$

Here, α is the penalty constant, $t(c_1)$ is the time of arrival at c_1, $|R_a|$ is the length of road R_a.

The route, as calculated by the Uniform Cost Search algorithm, is based on the current and predicted traffic, which changes with time. Vehicles may add in the desired route, vehicles may clear from the desired route and irregular trends may make the actual traffic much different from the predicted traffic. The route needs to be constantly adapted against these changing trends. *Continuous adaptation* by all vehicles in the traffic scenario enables vehicles to collaboratively make an efficient travel plan. This adaptation is done by replanning the route. Once the vehicle is on a road, it is considered that it will not turn back, even if turning back leads to a better route. Hence, maximum adaptation corresponds to replanning on reaching every crossing. The replanned route then reflects any changed traffic trends.

To test the working of this approach, a synthetic scenario was generated with a straight road with source/destination at the extreme ends. Initially, a very high traffic density was given to the road. Two alternative roads of unequal length were however also available to be taken and these finally merged again with the main road. Vehicles were continuously generated on both sides of the road. The vehicles first drove along the straight road. After some time vehicles were seen on the smaller alternative, whereas some kept going on the straight road to maintain the density. Still later, the larger alternative came into play and the vehicles used this for traversal as well.

An important factor of the algorithm is the parameter α which plays an important role in regulating traffic. The effect of changing this factor on the system performance with a large number of vehicles was studied. The algorithm was compared to a distance minimization Uniform Cost Search algorithm in which all the vehicles followed the same straight road and the other alternatives remained unused. The corresponding graph is given in Fig. 14.6. Increasing this factor encouraged vehicles to balance traffic densities across the different road options. An initial decrease points to the vehicles preferring the alternative roads when the main road is dense, which is the right strategy to follow. However, further increase of the factor encourages vehicles to take alternatives even though traffic on the main road is not very dense. This therefore increased the average time of traversal.

14.3.4 Reservations

Traffic systems may differentiate between important and nonimportant vehicles owing to their social importance. Roads may alternatively be seen as a business resource with possibilities of reserving a road or lane for a time exclusively or on shared basis. This is

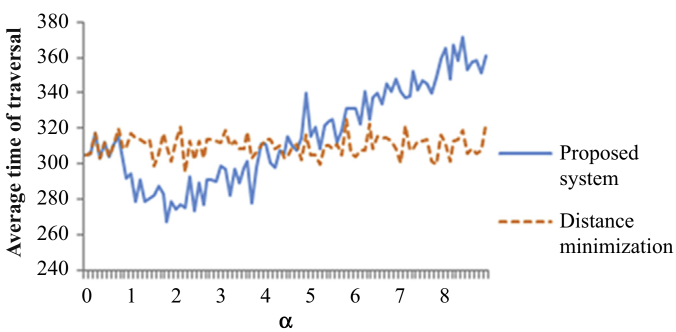

Figure 14.6 Comparative analysis of routing system for different values of α.

highly beneficial as *reservation* ensures reasonable travel speeds even though a general road may be heavily packed. This is especially important for roads in which the density of traffic is usually high or is expected to be very high because of some event. In such a case, it may be useful to have a road that can be reserved per a pricing model. At the same time, other general traffic can still move on other available roads. An important factor here is the *number of vehicles that may be reserved*. Reserving too few vehicles would make the road underutilized. Reserving too many vehicles, on the other hand, could make the traffic on the reserved road slower than the traffic on the nonreserved roads, giving no incentive for reservation. Assuming a high density of overall traffic in the system, it is further assumed that *p* percent of these vehicles were reserved.

A map was generated for simulation that had a straight road from the source to destination and a rather long and highly curved alternative road. The straight road was made a reserved resource. Hence, the reserved vehicles could travel straight on the road, whereas others would need to travel along the alternative, meandering, road. Unlike the map presented in Section 14.3.3, the long length of the alternative road in this scenario made the use of the straight road highly beneficial. The percentage of reserved vehicles *p* was varied and its effect on the average travel times of the reserved and the nonreserved vehicles was studied. The graph is shown in Fig. 14.7. Fig. 14.7 also shows cases with all vehicles reserved, in which they all used the straight road; and no vehicle reserved, in which they all used the diversion, and the main road was left unused. The graph shows the increase in travel time of the reserved vehicles as more and more of them travelled on the reserved road within the duration of simulation time. At the same time, the average travel time for nonreserved vehicles decreases as their number is reduced. This may help in determining the number of vehicles to be reserved, keeping the trade-offs matched.

A similar case may happen if *only a lane on a road is made a reserved resource* rather than a complete road. This makes it possible to use the existent road infrastructure for reservation as separate roads may not always be available giving reasonably alternate access. Reserved vehicles in such a case may be free to use general lanes and to *overtake* vehicles on the reserved lane but general vehicles may never be

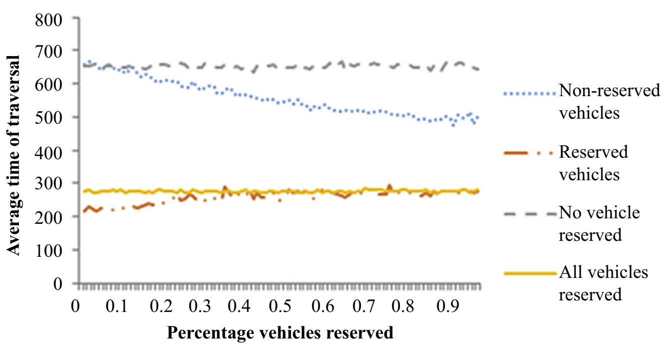

Figure 14.7 Comparative analysis of road reservation system for different percentages of vehicles reserved.

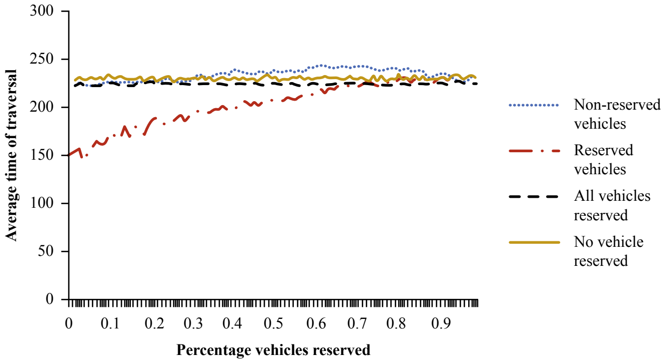

Figure 14.8 Comparative analysis of lane reservation system for different percentages of vehicles reserved.

allowed to move to the reserved lanes. Another manner in which the problem can be seen is in the case of emergencies. It would be viable to reserve a lane for an emergency service vehicle rather than for the vehicle to wait for other vehicles to give way at the time of travel. The concepts of lane reservation are the same as road reservation. A graph was plotted between the reserved percentage p and the time of travel for reserved and nonreserved vehicles. All reserved and nonreserved cases were also taken into account. The resultant graph is shown in Fig. 14.8. Here, the average time of traversal of vehicles increased as the number of vehicles reserved was increased. However, it should be noted that in this case there was no difference between all vehicles reserved or no vehicles reserved. The graph shows the same trend.

14.3.5 General Architecture

The general architecture of the simulator is given in Fig. 14.9. The architecture clearly shows the four modules discussed separately. Each one of them links to the other for information passing. Central information is maintained by the central information system. The initial settings or scenario may be given to this system as an initial specification file. The central information system is queried by all the other modules for information. The general architecture may be separately studied for vehicle subsystem, reservation subsystem, traffic lights subsystem and speed lane subsystem.

The vehicle subsystem has a route-planning algorithm that uses traffic information for deciding on the path. The lower-level planner uses traffic information to decide the motion of the vehicles. This may be to follow the vehicle in front (or simply to drive straight ahead), to change lane, to stop at a crossing, to start from a crossing or to turn at a crossing. Updated positions are always monitored and communicated to the central information system. For a lane change, the vehicle must be informed of the speed limits of the lane. Additionally, it must not be a reserved resource. Speed limits are always computed by the speed lane subsystem which gets all the traffic information from the central system for computation. The route planning subsystem must assess

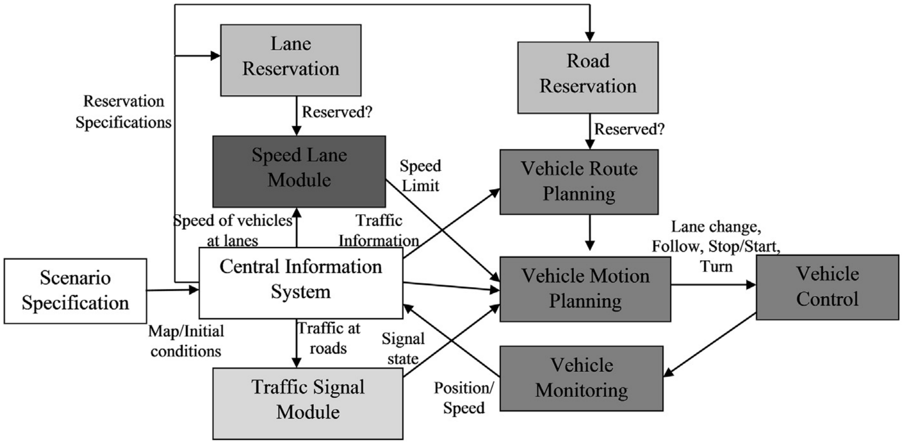

Figure 14.9 General planning architecture of the simulator.

if the road is a reserved resource or not. The reservation subsystem gives directions to the lane subsystem and the vehicle's route-planning module whether to use or not use the resource. Reservation may itself be separately handled by a system which is ultimately reflected in the central information system. The traffic lights subsystem operates the traffic lights based on the traffic behaviour on the various roads. The traffic-light state is communicated to the vehicles on approaching a crossing.

14.3.6 Simulations

So far, the mechanisms of the working of intelligent traffic lights, speed lanes, route planning and road/lane reservations were separately studied. All these concepts showcased benefits when compared to the current traffic management system. For traffic involving all these concepts at the same time, it can hence be expected that the individual system gains would all contribute to overall transportation system performance. The traffic simulation system is aimed at running a large number of diverse vehicles using all the modules stated earlier. The testing methodology in this section is to invoke all the modules and test the performance in complicated traffic scenarios.

To make the testing easy, a utility is created which can take an image representation of the environment and parse it to produce the road network map. It then becomes easy to make maps and use them for testing. The only parameter to be given to the simulator is the demand or the number of vehicles generated per unit time. This is needed for control of the induced congestion which the algorithm tries to eliminate. The locations of the vehicles, initial speeds, emergence time etc. are all set randomly. The initial and final positions are always kept at the extremity of the map so that the vehicles travel the maximum distance.

A number of maps were generated from the drawing utility tool and parsed to create a road network map. Large maps ensured that planning was a complex task. The

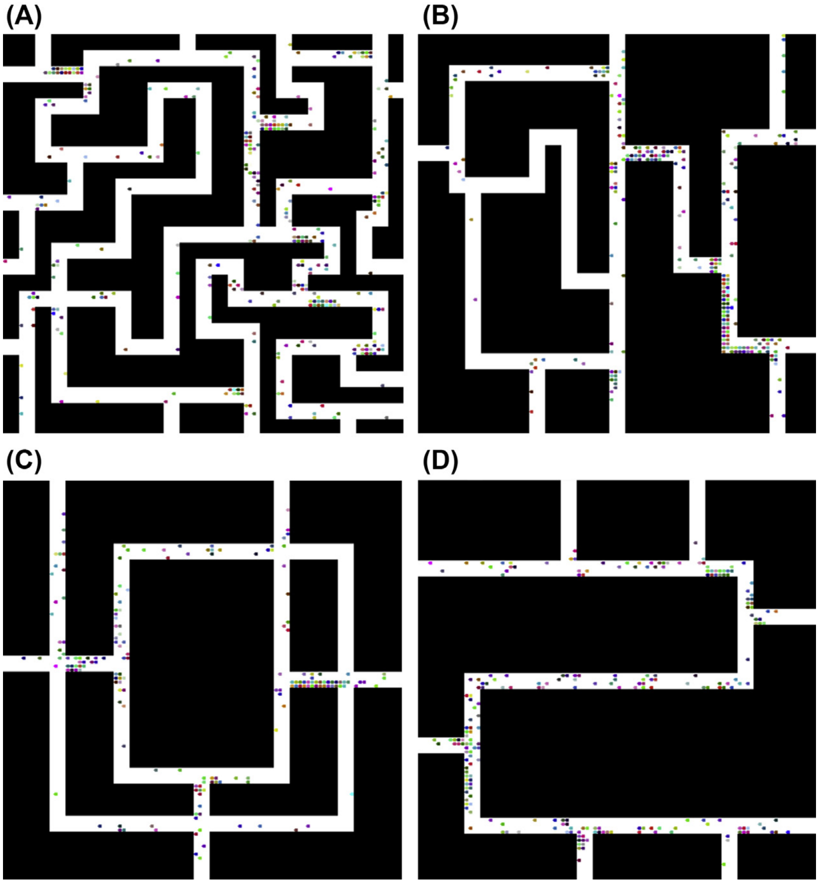

Figure 14.10 Simulation results.

densities were usually kept high as the benefits of the proposed system are particularly apparent in high-density circumstances. To better assess the working of the algorithm, the vehicles were plotted on this map with different colors. Screenshots of some of the simulations for test scenarios are shown in Fig. 14.10. For each simulation, it was observed that the vehicles were able to easily reach their goals while avoiding congestions and excessive waiting times. In a congested setting with too many vehicles asking to go though some central regions, queues were formed for some time when a red-light signal was apparent, but the queue cleared very quickly and the vehicles spread out to avoid congested areas.

The simulator measures a number of metrics which are indicators of the performance of the system. The primary performance indicator is the average travel time of the vehicles, which was the main metric used to assess the performance of the system. The other important metrics include the average travel distance and average travel speeds. To save space only one scenario is used for further analysis. The metrics for a different number of vehicles with all modules activated are shown in Fig. 14.11.

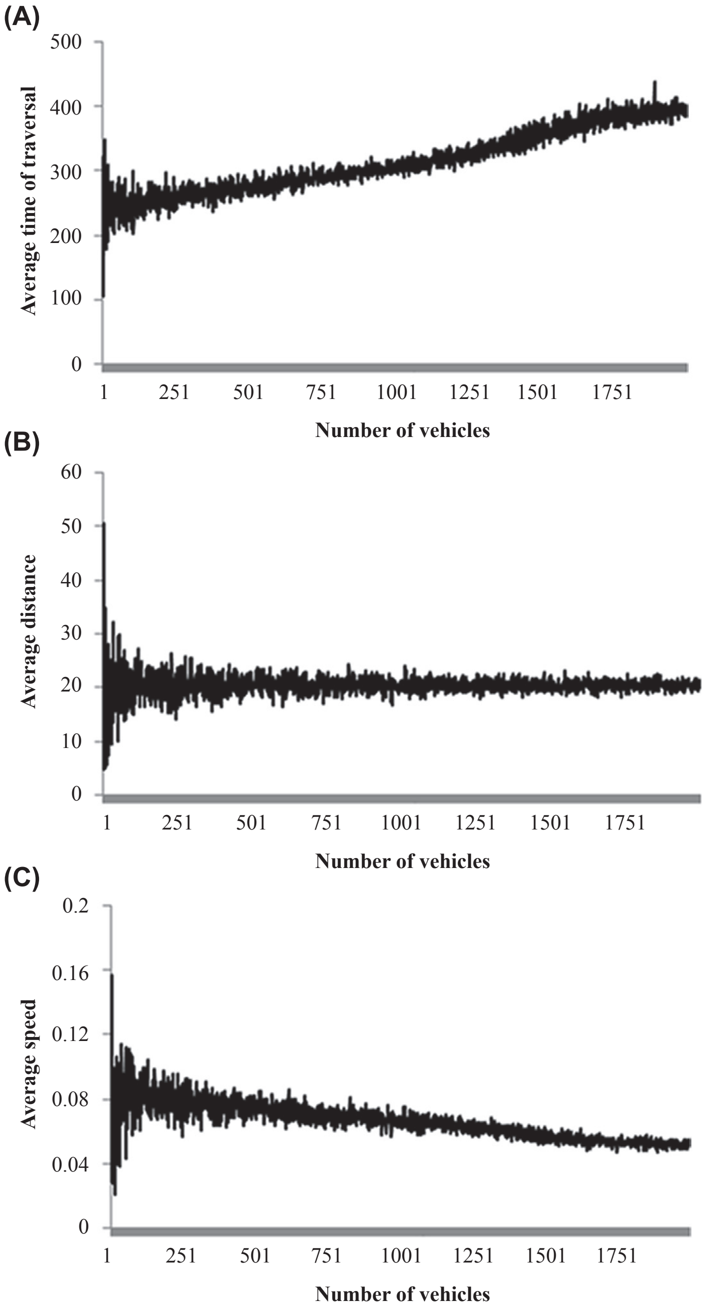

Figure 14.11 Analysis for integrated scenario. (A) Average time of traversal versus number of vehicles, (B) average distance versus number of vehicles, (C) average speed versus number of vehicles.

All units are arbitrary and specific to the simulation tool. The metrics can be mapped to real-world units by multiplying by suitable constants.

Scenario specifications such as the sources and goals of vehicles were randomly generated. This randomness contributes to the oscillations seen in Fig. 14.11. Based on a large number of simulations, it was observed that all the vehicles reached their destinations in acceptable times. Hence, it can be ascertained that the simulation tool developed for the purpose was able to cooperatively plan the paths of the different vehicles involved.

14.4 Congestion Avoidance in City Traffic

Large numbers of vehicles within a road network commonly give rise to congestion which is marked by a large drop in the average speed of the moving vehicles. As a result, every vehicle takes a considerable time to reach its final destination. On a particular road, congestion may be *recurrent* or *nonrecurrent* (Gordon, 2009). Although regular drivers are normally prone to adjust their departure times and routes for recurrent traffic, nonrecurrent traffic congestion is hard to predict and adjust to. Nonrecurrent congestion is caused by unusually high demand (like a sporting event) or suddenly low capacity (like an accident or a road closure).

An increasing amount of autonomy in vehicles and transportation management systems has given impetus to the possibilities of congestion avoidance. Although it is possible to locate, track and measure traffic density on various roads by intelligent agents concerned with road infrastructure, intelligent devices in vehicles are capable of collecting live data and using the same for planning purposes. This makes it possible to enable a vehicle to avoid roads in which congestion is likely to occur and to use alternative routes.

Traffic congestion (Verhoef, 1999; Maniccam, 2006) may be avoided largely by routing techniques, which tell the vehicle the route they need to travel. Presently installed devices and systems like Satellite Navigation only take static data. Unfortunately, this results in multiple vehicles using the same roads, which leads to congestion.

Here, first, the true state of the traffic system is analysed with an eye on possible future developments, and a traffic scenario prone to traffic congestion for everyday travel is assumed. Henceforth referred to as the *city traffic scenario*, this traffic scenario is analysed and a traffic-routing strategy is made for the guidance of vehicles. Experimental results are performed on the city (town as per local terminology) of Reading, United Kingdom. The key takeaways of the algorithm are summarized in Box 14.3. Box 14.4 summarizes the main concepts.

14.4.1 Problem Formulation and Scenario of Operation

The problem of study is to move a number of vehicles on a map such that congestion is avoided. The vehicles must not violate any traffic rules. Every vehicle may emerge on any part of the map at any time. The origin, destination or movement plan of any

Box 14.3 Key Takeaways of the Congestion Avoidance in City Traffic Approach

- Proposing *city traffic* as a scenario to study traffic congestion.
- Proposing the importance of considering *traffic lights* in decision-making regarding routes.
- Proposing a simple *routing algorithm* that eliminates the high density of traffic and hence minimizes congestion.
- Stressing *frequent short-term replanning* of the vehicle in place of long-term (complete) infrequent replanning.

Box 14.4 Key Concepts of the Congestion Avoidance in City Traffic Approach

- **Assumptions**
  - Vehicles have very diverse speeds
  - Nonrecurrent traffic (does not follow historical traffic patterns)
  - *City* traffic scenario
- **City Traffic Scenario**
  - *Infrastructure*: Many short-length roads (alternative roads) intercept each other in city traffic, meaning very computationally expensive routing; unlike highway traffic with fewer roads and longer roads.
  - *Vehicle Emergence*: Many entry/exit points are located at road ends/between roads in city traffic, because of which new vehicles constantly enter and anticipation not possible; unlike highway traffic which has distant entry/exit points and new vehicles do not much invalidate anticipated plans.
  - *Planning Frequency*: Low anticipation invalidates long-term plans in city traffic, while high anticipation favors long-term planning in highway traffic.
- **Hypothesis: Make frequent effective short-term plans**
  - *Frequent*: Constantly adapt to changes, replan at every crossing
  - *Effective*: Minimize (1) expected travel time, (2) expected traffic density, (3) expected time to wait at crossings
  - *Short Term*: Limit computational requirement. Plan for a threshold distance from the source, assume it is possible to reach the goal from the planned state. Like human drivers, always see the *current* traffic and take the best route *towards* the goal, assuming no dead ends.

vehicle is not known by any other vehicle. This means there is a provision for manual vehicles in the traffic scenario. U-turns can only be taken from a traffic crossing and not in the middle of the road. The efficiency of this routing system is judged by the average time of travel of the vehicles. This metric is considered to reflect the magnitude of congestion that a vehicle faces during its travel. The algorithm is motivated by the characteristic scenario on which it operates, which is explained in detail in the following subsections.

14.4.1.1 City Scenario

The scenarios of moving within a *highway map* and a *city map* are clearly different. Both, however, place stress on judiciously selecting the roads to travel on and forecasting the scenarios well in advance to avoid traffic congestion. However, the former scenario has long highways which, if entered, need to be followed for a significantly long time before an alternative path may be available, whereas the latter has numerous alternative roads from which a vehicle may diverge and reconnect through any other close cut-in. The other point of difference lies in traffic emergence. Highway scenarios have distant entry and exits points, whereas in city traffic any vehicle can enter or leave from any road. Thus, within a city, anticipation may not always help as it accounts for only recurrent traffic (in forecasting-based systems) (Dia, 2001; Kirby et al., 1997) or intelligent vehicles which are on the road and the travel plan for which is known (for anticipatory routing systems) (Weyns et al., 2007; Kaufman et al., 1991). In reality the vehicles may emerge from car parks (or homes) located at any point along any road and in doing so affect the entire network plan.

The difference between highway traffic and city traffic emphasizes the fact that while in highway scenarios it may be advisable to make *long-term plans*, the same are not so useful for city traffic. In highway scenarios the vehicles can be expected to stick to their anticipated plans, thereby indicating which highway to follow. In city traffic, on the contrary, vehicles may make *very frequent changes* in travel plan due to the variety of options in terms of the roads to take to reach their destination. Because the number of vehicles is large, the total changes may be too large for any system to monitor and every change will affect all vehicles, which makes the system too dynamic to handle. Present approaches (eg, Claes et al., 2011) limit the changes and only accept the changes which result in a significant improvement and hence control the highly dynamic nature of the problem in this way. Here, a part of the road map of Reading, United Kingdom, is taken as the city map given in Fig. 14.12.

Routing may be classified into *centralized approaches* (Kuwahara et al., 2010) and decentralized approaches (Pavlis and Papageorgiou, 1999). *Decentralized approaches* consider every vehicle separately during plan generation and are hence able to generate

Figure 14.12 Map of Reading, United Kingdom, used for experimentation.

a travel plan in a short time. During planning of each vehicle, decentralized techniques may prefer (1) not to account for another vehicle's motion, (2) to predict the motion of other vehicles or (3) use traffic forecasting information from the historical data (Taniguchi and Shimato, 2004). Method (1) leads to high traffic congestion and method (3) does not account for nonrecurrent traffic. *Microsimulation* is a common tool for method (2) wherein it is assumed that the travelling information of all the vehicles is available and the system operates by simulating the different possible plans. The method has limitations including the fact that it is computationally difficult to simulate a large number of vehicles for every replan of a vehicle's trajectory or in the case of any new vehicle entering. If a vehicle replans, the plans of some other vehicles may get affected and it may sometimes take a long time for vehicles to obtain their best plans. All vehicles on the road need to be intelligent and the assumption is usually that they have similar driving speeds. In addition, simulation uncertainties can become very large with time. These uncertainties are especially large when accounting for overtaking and traffic signals. All this puts an emphasis on long-term plans being of less use for city traffic.

Although a high number of roads or high connectivity leads to a significant variety of travel options, it further makes the problem computationally expensive. Cities are normally large. Most studies are restricted to traffic over only part of the overall city map.

14.4.1.2 Inferred Hypothesis

Understanding the stated points, it must be noted here that it is important to make *frequent effective short-term plans*, rather than making plans which are too long term, investing in heavy computation and hence limiting the planning frequency. From a simulation tool perspective, the computing infrastructure that simulates, renders and moves every vehicle is limited, and it has to give simulation results within limited times. As a result, researchers usually have to limit the frequency of replanning for each vehicle, and this has a considerable impact on the study.

From the perspective of a physical system, every vehicle has its own computing infrastructure which interacts with the other computing infrastructures to get information. In a scenario in which the static map is itself complex, loading the vehicle with excessive information on the motion of the other vehicles makes the computing even more difficult. This is of less use when considering that long-term plans are uncertain and hence the real/actual information is likely to change.

14.4.1.3 Other Scenario Specifics

Traffic systems in most countries consist of vehicles which travel with nearly the same preferred speeds. However, the study is aimed at scenarios in which the vehicles may greatly differ in their preferred speeds. The difference in present-day traffic mainly reflects the urgency, driving capability and experience of the drivers. Technology has led to modern day vehicles to be classified as autonomous, semiautonomous or manual vehicles. The first may typically see vehicles that differ in speeds as per size, price, features, sensing and control algorithms.

Considering city-based traffic, it is further considered that a major proportion of the roads are two lanes with one lane each for inbound and outbound traffic. With diverse speeds, it is naturally unpleasant for a high-speed vehicle to be following behind a low-speed vehicle for a large part of the journey, in which there is no multilane to overtake by lane changes. Hence, it is allowed for vehicles to travel on the 'wrong' side of the road for some time to complete an overtaking operation.

14.4.1.4 Decentralized Anticipatory Routing

A significant attempt is made to use a decentralized anticipatory approach to vehicle routing. In a related work, Claes et al. (2011) presented a system wherein every vehicle considers all possible routes before selecting a 'best' route for its journey. The authors realized a formula to convert the anticipated traffic density into an average travel speed. This extends the work of Weyns et al. (2007), who used traffic microsimulation to compute the anticipated traffic speed. *Replanning* is done after some time steps for every vehicle. In light of the discussions, the limitations of the approach are too infrequent replans, the impossibility of computing every possible route in real time for large maps, the assumption that every vehicle is intelligent, no consideration given for traffic lights or overtaking and finally all vehicles are assumed to have the same preferred travel speed which makes conversion of traffic density to predicted speed possible. Most of these limitations might however hold if the complete map was itself small.

The attempt is to present a fairly simple system not making assumptions which may not hold true in the real world. In Section 14.4.3 it is shown how this may lead to a better performance in city traffic. In fact, the complete system may be implemented by the adoption of a simple changeable message sign (CMS) at every road end, along with some detectors (such as an array of loop detectors, a counter for vehicle entry/exit etc.) to measure traffic density.

14.4.2 System Working

This section describes the entire system used to route and move the vehicles. The system is designed such that congestion is avoided as much as possible, while it is assumed that the density of vehicles at every road can be sensed.

14.4.2.1 Traffic Simulation

Vehicle motion is done using an *Intelligent Driver Model* (Treiber et al., 2000). The model states the manner by which one vehicle follows another vehicle depending upon the preferred driving speeds, operational speeds and available separation distances. The preferred speed of the vehicle V travelling along road R_{ij} connecting nodes v_i and v_j is taken to be $v\text{pref}_{ij} = \min(s, \text{speed\_limit}_{ij})$, in which s is the preferred speed of the vehicle V. speed_limit_{ij} is the maximum allowable speed on the road R_{ij}. Because the road traffic is diverse, the vehicles vary in their maximum speed s.

Considering a high diversity, a lot of *overtaking* is possible solely by lane-change mechanisms. Hence, a vehicle must always be ready to overtake a slow vehicle in front and to be itself overtaken by an even faster vehicle to the rear. For decision-making regarding lane changes, time to collision is used as a metric (if the vehicles continue to travel at the same speed).

If the vehicle is travelling close to its maximum speed limit $vpref_{ij}$ it may further attempt to stay in the left hand lane (to facilitate others to easily overtake it, in left-side driving countries − United Kingdom/Japan style considered) unless it sees a slower vehicle ahead of it in the left-hand lane. In such a situation naturally, no question of overtaking arises whilst a vehicle to the rear has already requested to overtake. Overtaking on the right is preferred as compared to overtaking on the left in case both options are available and likely.

For simulation purposes, *traffic lights* are assumed intelligent in that they know the number of vehicles at each entry point and their time of arrival. The traffic lights do not change in a cyclic manner, but allow traffic to flow from the direction of the vehicle with the longest waiting time. The switching frequency of the traffic lights is taken as a maximum of mtim. If no vehicles are waiting to cross the road, the traffic light for which is currently green, and some other road has vehicles waiting to pass through, the traffic lights would change before the normal scheduled time. mtim is a constant and is set using simulations, such that it allows enough vehicles to pass through in a heavily congested traffic scenario. The factor is only of importance when far too many vehicles are waiting to cross an intersection; as in other cases, the queue clears well-before this factor comes into play.

14.4.2.2 Single-Lane Overtaking

In case the vehicle is travelling on a road on which a single lane exists for each side of the traffic, it may be undesirable to follow a slower vehicle in front. Hence, the vehicle is allowed to move onto the wrong side of the road to overtake the slower vehicle and to then return to the left-hand lane. Such an overtaking is termed as *single-lane overtaking*.

For overtaking, it is essential that the vehicle being overtaken is travelling almost at its preferred speed which is slower than the preferred speed of the overtaking vehicle. In addition, the vehicle being overtaken must itself not currently be overtaking another vehicle, and any other vehicle on the wrong side of the road (if any) must not be overtaking. An overtaking vehicle is projected to be accelerating till it reaches its preferred speed (or until overtaking completes) while overtaking. Separations from the vehicle being overtaken, to any vehicle on the wrong side of the road (if any), and the vehicle ahead of the one being overtaken (if any) are checked at every instance. All these must be greater than the preferred separations (as per the intelligent driver model) at all times during the overtaking procedure. Overtaking cannot happen if (by projections) it cannot be completed before the end of the road. If all the conditions hold good, overtaking then takes place. A simulated overtaking scenario is shown in Fig. 14.13.

It may be interesting to observe that the applied overtaking mechanism assumes *no cooperation* with other vehicles. In simple words, the other vehicles may assume that

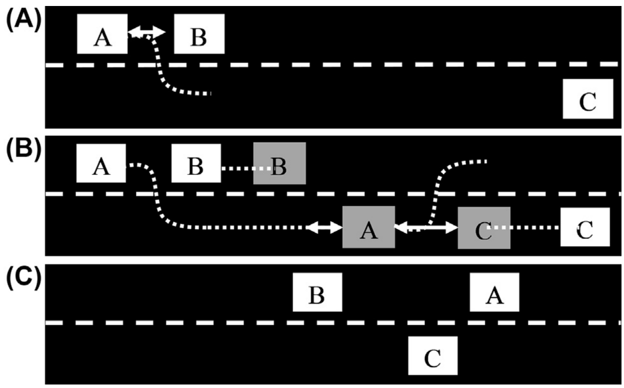

Figure 14.13 Single-lane overtaking. (A) *A* checks feasibility to overtake *B* while *C* is coming from opposite end. (B) Projected positions of vehicles when *A* is expected to lie comfortably ahead of *B*. (C) Completion of overtake. Arrows indicate separation checks. Because *A* and *C* are moving in opposite directions, needed separation is much larger.

the overtaking vehicle is absent and move normally thereby still making the required separation with all the vehicles. The only exception is that other vehicles may not accelerate. In the real world the oncoming vehicle or the vehicle being overtaken may slow down as an act of cooperation. The important decision of whether overtaking is to take place is done solely by the overtaking vehicle without assuming cooperation, and even if an error is made the oncoming vehicle and the vehicle being overtaken compulsorily slow down to facilitate the overtake.

14.4.2.3 Vehicle Routing

Routing deals with the route selection of the vehicles. The *frequency of planning* is a key aspect which, per the hypothesis, needs to be as large as possible for efficient congestion avoidance. Considering that taking a U-turn in the middle of the road is not allowed, the earliest a vehicle can react to any change of plan is before a crossing. The planning should be done well before reaching the crossing so that the required lane changes are made, traffic lights are read and suitable indicators are given before making the required turn at the crossing. Hence, the maximum magnitude of replanning corresponds to planning the vehicle before every crossing.

The basic planning algorithm employed is A*, which is a search algorithm that finds a path from a given source to a given goal depending on a cost function supplied in the solution design. The A* algorithm finds a solution by constantly expanding nodes with the best expected cost from the source to the goal. The historic cost hist(v_j) of a node v_j refers to the actual cost from the source to reach that node per the designed cost function. The heuristic cost heuristic(v_j), on the other hand, estimates the cost from the current node v_j to the goal. The algorithm searches by constantly expanding nodes based on these costs.

Per assumptions, it is computationally very expensive to plan the entire route. An inspiration is taken from the manner in which human drivers plan their route. Drivers can reach their destination by a simple attempt to select the roads that make the vehicle head *towards the goal*. In case multiple such roads are possible, *short-term planning* may be done to reach some point by the best manner, beyond which an approximate travel cost may be assumed. However, it is important to be assured that the selected point is actually connected to the destination, without having the vehicle turn back or go by a long route. Although doing so the travel plan is made suboptimal, it is a compromise to the computational cost.

Hence, the A* algorithm stops if the historical cost is more than *maxHistorical* and the current node (best in the open list) is termed as the goal, in which the factor *maxHistorical* controls the computational cost. A low value of this factor makes the routing algorithm largely heuristic, in which heuristic estimates determine the route, whereas a large value may be too computationally expensive. The factor is given the highest value as per the available computation. In the preliminary version of the algorithm, a heuristic search (which is nonoptimal but very fast) was used to ensure that the subsequent motion from the node does reach the goal without having the vehicle move backwards. However, experimental results showed that such a path was always possible in the experimented scenarios and hence the check was removed, thereby saving on the computational cost. Having high connectivity, it is natural that from any point the vehicle would be able to reach the destination by travelling towards it.

Let the historic cost of node v_j be given by $\mathrm{hist}(v_j)$ and let e_{ij} be the average length of the road R_{ij} from node v_i to node v_j. The historic cost is given by Eq. [14.9]. As the cost minimizes both the density of the road network as well as the number of traffic lights that the vehicle may encounter, the method is called *density-based routing with traffic lights*.

$$\mathrm{hist}(v_j) = \mathrm{hist}(v_i) + \frac{e_{ij}}{S\left(v\mathrm{pref}_{ij}, n(R_{ij})\right)} + \eta(R_{ij})\cdot \mathrm{mtim}(R_{ij}) \qquad [14.9]$$

Here, $S(v\mathrm{pref}_{ij}, n(R_{ij}))$ is a function that predicts the average speed of a vehicle per the current traffic scenario at the road R_{ij} having a current number of vehicles $n(R_{ij})$. In the present approach this is given by Eq. [14.10].

$$S\left(v\mathrm{pref}_{ij}, n(R_{ij})\right) = \begin{cases} v\mathrm{pref}_{ij} & n(R_{ij}) \le n_{th} \\ \dfrac{v\mathrm{pref}_{ij}}{n(R_{ij})/k\cdot n_{th}} & n(R_{ij}) > n_{th} \end{cases} \qquad [14.10]$$

Here, it is assumed that the operating speed is inversely proportional to the density. $\eta(R_{ij})$ is the fraction of traffic-light changes that the vehicles at road R_{ij} wait for before getting a chance to get through the traffic lights. $\mathrm{mtim}(R_{ij})$is the average time of wait at the traffic light for a single change. $\mathrm{mtim}(R_{ij}) = 0$ if R_{ij} does not end at a traffic light. The factor n_{th} accounts for the number of vehicles that may leave within the traffic-light change as per the factor $\eta(R_{ij})$, whereas the factor k relates density with the driving speed in dense traffic.

The heuristic cost is given by Eq. [14.11].

$$\text{heuristic}(v_j) = \frac{\|v_j - \text{Goal}\|}{\min\left(s, \max_{i,j}\left(\text{speed\_limit}_{ij}\right)\right)} \quad [14.11]$$

Here, $\|v_j - \text{Goal}\|$ denotes the distance between the node v_j and the Goal measured using the coordinates of the two places on the road map. s is the preferred driving speed of the vehicle. The term $\max_{i,j}(\text{speed\_limit}_{ij})$ is the maximum speed possible on any road, which would point to the maximum allowable speed in the transportation network. Note that the heuristic function is admissible and assures optimality of the A* algorithm. However, the expansion of the A* algorithm is proportional to the difference between the actual cost and the heuristic estimates, which is high for the presented approach. This results in a significant number of nodes being expanded. The output of the A* algorithm is a *route* consisting of the roads that the vehicle must follow. A simulated planning procedure showing the iterations of repetition is shown in Fig. 14.14.

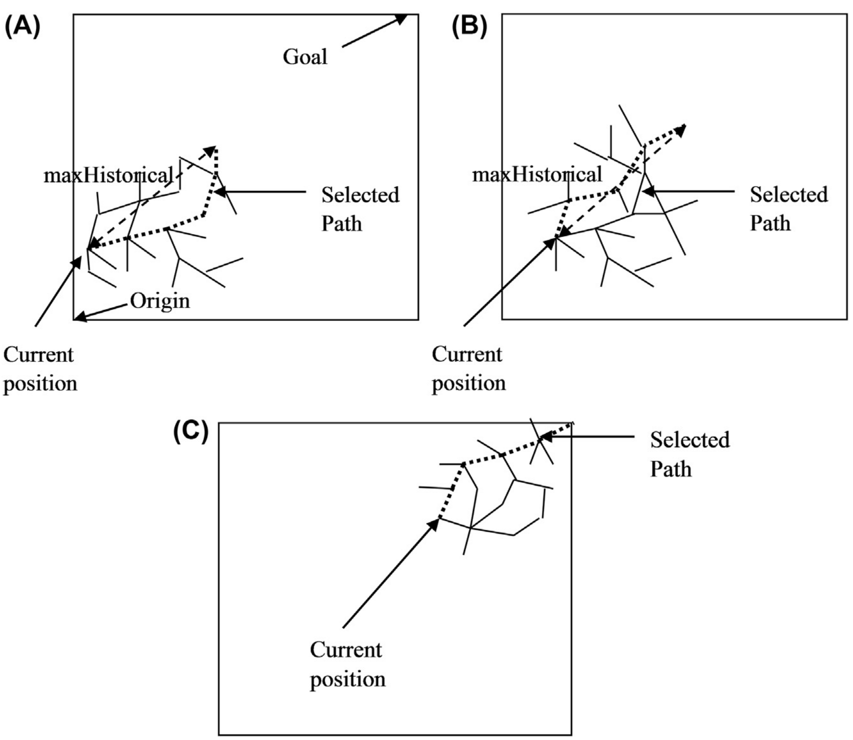

Figure 14.14 Routing by replanning at every crossing. (A) From current position, vehicle plans towards goal and after *maxHistorical* cost stops the current search and moves by best path. (B) After reaching next crossing, change of plan takes place as per new information available. (C) Vehicle finally reaches a point from where the goal is near.

14.4.3 Experimental Results

14.4.3.1 Initialization

Experiments were done on a traffic simulator based on an intelligent driver model and other features as discussed in Section 14.4.2. Experiments were done on a part of a road map of Reading, United Kingdom, which is shown in Fig. 14.12. The map was obtained from (Openstreetmap, 2011). A Depth First Search algorithm was used to eliminate isolated nodes. The processed map had a total of 7765 road nodes. Major roads were all assumed double lanes, whereas the general roads were all considered single lanes. Speed limits were fixed to 30 miles per hour or 40 miles per hour. The left-side driving rule was followed.

Traffic is produced in the road network by randomly generating an origin–destination matrix. The number of vehicles per second that enter the traffic scenario is taken as a human input using which vehicles are generated continuously for 10 min. Henceforth, the generation of vehicles stops but the simulation runs till all vehicles reach their destinations. The origins and destinations are preferred to be on the opposite sides of the map separated by a displacement of more than the radius of the map. The origin is selected by using a Gaussian distribution with the mean centred outside the map's central point by a magnitude of half the radius. The angle of origin to the map's centre (θ) is chosen randomly. The destination is also chosen from a Gaussian distribution with its mean at half the map's radius. The angle of destination to the map's centre is chosen from a Gaussian distribution with mean located at $\pi + \theta$. The speed limit of the individual vehicles is selected from a uniform distribution varying from 20 miles per hour to 40 miles per hour.

14.4.3.2 Alternative Methods

The strict constraint in the choice of the alternative methods for comparison was that no communication must exist between the vehicles or between all the vehicles and a central transportation system. Most research work on microsimulations, replanning etc. hence gets eliminated. Further, because the approach is for nonrecurrent traffic, most of the learning-based systems get eliminated. Based on these assumptions, a limited choice of methods is available, which were experimented on. However, further issues relate to the diversity of the vehicles in terms of travel speeds which make many of the alternative methods unacceptable.

Comparisons of the technique have been carried out with a variety of other methods. Each basic method has two modes of operation, a static case wherein the route is planned initially and the same is followed unaltered till the goal is reached; and a dynamic case wherein the routing takes place at every intersection.

The first method employed is the *optimistic fastest routing strategy* used for static planning. The strategy computes a route by minimizing the expected time of completion of the journey, which is given by Eq. [14.12].

$$\text{cost (optimistic)} = \sum_{e_{ij} \in \text{Route}} \frac{e_{ij}}{v\text{pref}_{ij}} \qquad [14.12]$$

The second strategy used for comparison is the *pessimistic fastest routing strategy* which is similar to the optimistic fastest routing strategy with the difference that the cost to be minimized is given by Eq. [14.13]. The attempt is to prefer roads which have a higher number of lanes. Here, $w_{ij} = 1/\text{lanes}(R_{ij})$, $\text{lanes}(R_{ij})$ is the number of lanes in road R_{ij}.

$$\text{cost (pressimistic)} = \sum_{e_{ij} \in \text{Route}} \frac{w_{ij} \cdot e_{ij}}{v\text{pref}_{ij}} \tag{14.13}$$

The next strategy used is the *Traffic Messaging Channel* (TMC, Davies, 1989). In this strategy, every vehicle, on reaching the road segment end, informs the system about the average speed at the particular segment and this is used for planning other vehicles. Considering the simulation scenario, the cost minimized by this planning is given by Eq. [14.14].

$$\text{cost (TMC)} = \sum_{e_{ij} \in \text{Route}} \frac{e_{ij}}{\min\left(\text{TMC}_{ij}, v\text{pref}_{ij}\right)} \tag{14.14}$$

TMC_{ij} is the average speed as known by the TMC system. The update is done as per Eq. [14.15].

$$\text{TMC}_{ij}(t) = \begin{cases} (1 - \text{lr}) \cdot \text{TMC}_{ij}(t-1) + \text{lr} \cdot v_{ij}^{\text{avg}} & v_{ij}^{\text{avg}} < v\text{pref}_{ij} - \varepsilon \\ \text{TMC}_{ij}(t-1) & \text{otherwise} \end{cases} \tag{14.15}$$

v_{ij}^{avg} is the average speed of the vehicle at road R_{ij}, ε is a small number. Eq. [14.15] avoids vehicles with lower preferable speed to slow the TMC known average values, if the actual traffic is moving reasonably fast. lr is the learning rate.

These three strategies find the route from source to goal which does defy the assumption that the map is too complex for timely computing the route from the source to goal. This was, however, done only for comparative purposes. The time was large enough to disallow continuous replanning.

The next set of alternative methods belongs to the *dynamic domain* in which vehicles are replanned at every crossing. Considering the computation time, in each case replanning is done for short durations as explained in Section 14.4.2.3. The four methods are experimented, namely, TMC, density, TMC with traffic lights and density with traffic lights. The last method is the proposed method as discussed in Section 14.4.2. Density-based planning is same except for the fact that it disregards the traffic-light factor. The TMC method is the dynamic equivalent of the static TMC method. TMC with traffic lights has an additional cost on encountering traffic lights. The cost functions for each of these methods are given by Eqs [14.14], [14.16]–[14.18].

$$\text{cost (density)} = \sum_{e_{ij} \in \text{Route}} \frac{e_{ij}}{S\left(v\text{pref}_{ij}, n(R_{ij})\right)} \qquad [14.16]$$

$$\text{cost (TMC with traffic lights)} = \sum_{e_{ij} \in \text{Route}} \frac{e_{ij}}{\min\left(\text{TMC}_{ij}, v\text{pref}_{ij}\right)} + \eta(R_{ij}) \cdot \text{mtim}(R_{ij}) \qquad [14.17]$$

$$\text{cost (density with traffic lights)} = \sum_{e_{ij} \in \text{Route}} \frac{e_{ij}}{S\left(v\text{pref}_{ij}, n(R_{ij})\right)} + \eta(R_{ij}) \cdot \text{mtim}(R_{ij}) \qquad [14.18]$$

14.4.3.3 Comparisons

The metric that judges the effectiveness of the algorithm is the average time to destination. The results for increasing demands for various routing strategies are shown in Fig. 14.15. The algorithm was tested for a maximum of 45 vehicles per second which meant that there were a total of 27,000 vehicles. The general trend expected was an increase in the average time of completion of the journey per vehicle, which is visible in the graph barring a few regions. The difference in trend is due to the fact that for every demand, different origins, destinations and speeds were selected.

From Fig. 14.15, it can be easily seen that the proposed method performs best for all demands. The trend is closely followed by the TMC method with traffic lights. Clearly, considering traffic lights was beneficial as density and TMC methods with the traffic-light factor proved to perform better. An anomaly is the static TMC performing better than that the dynamic TMC. However, although the static TMC invested heavily

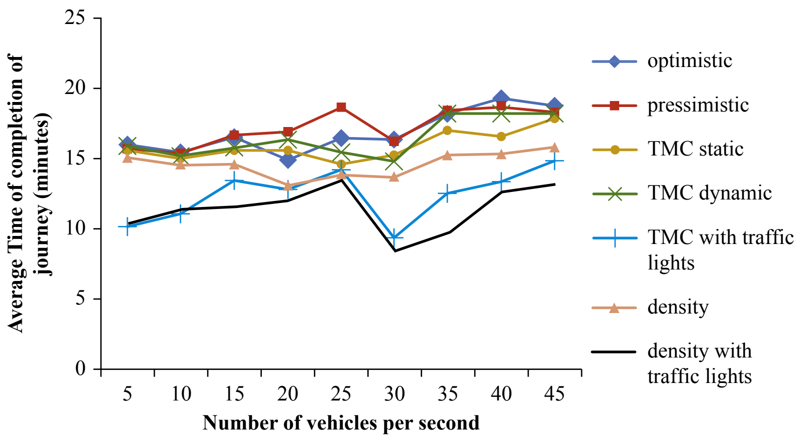

Figure 14.15 Average time of completion of journey for various algorithms and demands.

on computation at the start to find the best route from source to goal as per the set metric, the dynamic TMC plans only up to a point ahead. Hence, restricting the search for computational betterment has a payoff for the algorithm when taking longer routes. Further, at higher demands it takes a little time for the traffic level to rise on the popular roads. Later vehicles prefer alternative routes, thereby keeping the congestion level the same or balanced. Because part of the city map was simulated, the static congestion level was enough information as it did not change much.

Although the time of completion of journey was the sole metric of use which was optimized, it is also seen how the different routing strategies behaved in terms of total distance of travel. The graph showing the distance of travel for different demands is given as Fig. 14.16. For large demands, the proposed method had the shortest distance, whereas the largest distances were recorded by the optimistic and the pessimistic strategies. The distances for these strategies were largest due to the fact that faster strategies assumed roads with a large number of lanes and higher speed limits would lead to the shortest travel time. These roads usually have a high degree of congestion, and hence the assumption is incorrect.

The reason for longer time of travel for the dynamic TMC is visible in the distance graph which took longer routes. The TMC group of algorithms though had a better view of the applicable traffic speed. Density-based methods taking shorter distances indicate the cooperative measure of vehicles in the front for vehicles behind, in case the main route important for the vehicles behind is congested. The algorithms including the traffic-light factor show low distance indicating that it was precomputed that the majority of the time would be wasted at traffic lights.

The travelling speed is simply distance upon time, and hence it is simple to understand. The trend for various algorithms is given in Fig. 14.17. Considering that a significant portion of the time was wasted while waiting at crossings, the actual travel speeds were much higher. The optimistic and pessimistic algorithms emphasized taking wide roads which were longer, and hence the average speed was sufficiently fast even though it was reasonably less than the allowed speed limit. Other strategies emphasized taking shorter routes which were less congested, and hence a decent travel speed could be maintained.

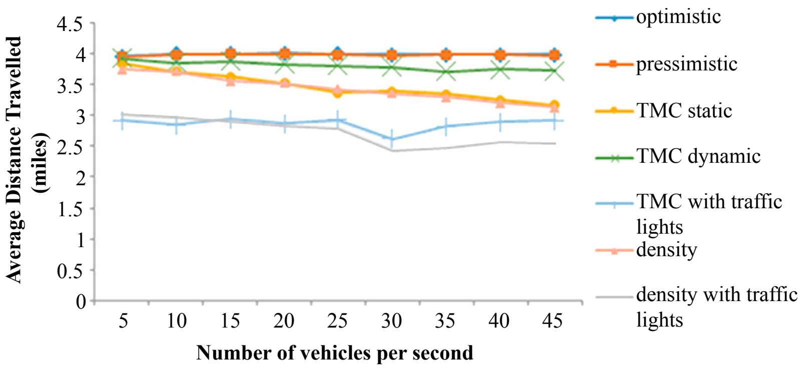

Figure 14.16 Average distance travelled for various algorithms and demands.

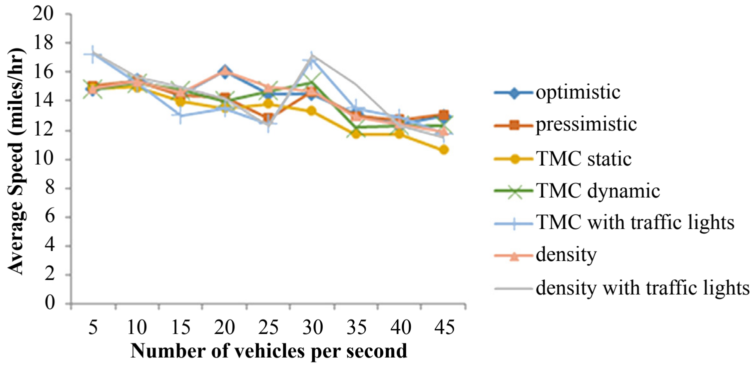

Figure 14.17 Average speed for various algorithms and demands.

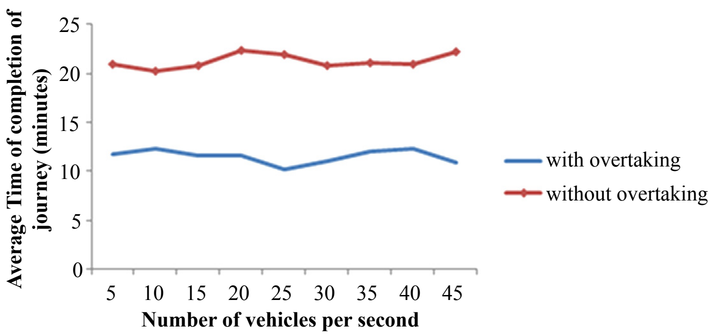

Figure 14.18 Average time of completion of journey with and without single-lane overtaking.

14.4.3.4 Analysis of Single-Lane Overtaking

An important feature of the algorithm was the ability of having overtaking in single-lane roads. Even if a single slow-moving vehicle is somewhere ahead in the lane, the entire lane traffic could suffer even in low-congestion areas. Most roads being single lane make overtaking impossible without this feature. The average time of journey is shown in Fig. 14.18. It can be clearly seen that single-lane overtaking resulted in a great boost to travel time. Without the feature, the main traffic scenario was primarily that all vehicles followed a slow vehicle ahead.

14.5 Summary

The chapter addressed the problem of managing traffic in a transportation system with diverse speed vehicles. Traffic density is constantly increasing, and this puts a lot of stress on the present transportation infrastructure. Semiautonomous vehicles with the option of communicating with other vehicles, road infrastructure and transportation management units are capable of efficiently planning themselves resulting in higher transportation efficiency. In the first part of the chapter, some of the various possibilities have been addressed, whereas the aim is to build on the existing traffic management system by making each of its components intelligent and efficient. The system was broken down into four main modules: traffic-light management, route planning, speed-lane management and reservation. Each of these concepts resulted in better management of traffic, reducing the average traversal time of vehicles. The resulting system is a dynamically managed traffic system which attempts to make traffic flow as efficient as possible.

Diversity in vehicle speeds makes systems behave differently from general expectations. Here an attempt was made to investigate the effect of increased diversity of vehicular speeds on overall transportation performance. Slow vehicles can lead all traffic in a lane to be slow, resulting in reduced efficiency, and this has to be managed by the transportation system. In the simulations, it was seen that slow vehicles do affect the travel efficiency of the fast vehicles and the effect is unavoidable; however, the effect is much lower in lower-density traffic wherein fast vehicles have the option to overtake by lane changes. Hence, there is an advantage in eliminating high traffic density on roads, which was a key objective of the routing system. Alternatively, on high-density roads, speed limits need to be intelligently adapted so as not to punish high-speed vehicles too much by making them drive in low-speed lanes while also not forcing vehicles to follow a slow vehicle ahead. Reservation signifies social diversity of vehicles. Expected dense traffic with diverse vehicles cannot be guaranteed a reasonable performance unless social diversity of vehicles is exploited as an additional factor.

In the second part of the chapter a method was presented to solve the traffic congestion problem, accounting for the factors of traffic density and traffic lights for a city transportation infrastructure. The solution attempted to make frequent short-term plans for each vehicle. The decentralized nature of the algorithm enabled its scalability. With this, the highly uncertain nature of long-term plans was also stressed based on which no decision-making can be done. The algorithm performance was reasonably better when the vehicles were allowed to overtake in a single lane. Experiments showed that the traffic lights played a vital role in planning.

Any routing algorithm for vehicles has a strict decision point regarding preferring shortest path to goal, fastest roads or reducing the waiting time at crossings. Considering the nature of the problem in which additional vehicles may pop up anytime and anywhere and known vehicles may change their plans without notice, it is impossible to predict these metrics for all roads. High diversity in terms of vehicular preferred speeds makes the choices even more difficult. Experiments show that the proposed algorithm is the best trade-off between these selections. Frequent replanning ensures plans are adaptive to changing traffic.

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